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Alzheimer Disease Prediction Through Guided Predictive Modeling With Machine Learning

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Abstract

Alzheimer's disease is a progressive neurodegenerative disorder characterized by the accumulation of misfolded brain proteins, especially beta-amyloid plaques, resulting in cognitive deterioration and memory impairment. However, there has been no effort of early detection to facilitate prompt intervention and preventive strategies. This research fulfills this essential need by employing the Open Access Series of Imaging Studies (OASIS) dataset supplied by the Alzheimer's Disease Neuroimaging Initiative (ADNI). The research employs the Cross-industry Standard Process for Data Mining (CRISP-DM) methodology to create and assess a classification model utilizing Artificial Neural Networks (ANN). The model attains a remarkable accuracy rate of 96%, exhibiting elevated precision, recall, and F1-scores across all categories. A 10-fold cross-validation technique was utilized to assess the model's robustness, resulting in an average accuracy of 90.7%. These findings underscore the efficacy of artificial neural networks in identifying Alzheimer's disease in its initial phases. This research utilizes advanced data mining approaches to improve predictive capacities and highlights the promise of machine learning in tackling intricate healthcare issues.

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1. Introduction

Every human being will eventually age and face distinct age-related health difficulties. Cognitive decline is a prevalent ailment among older persons, and it is commonly related with Alzheimer's disease. This disease is the most common neurodegenerative ailment, and it frequently affects the elderly, with the risk increasing with age. In general, adults over the age of 65 are more likely to develop Alzheimer disease than younger ones [1]. AD is distinguished by the formation of beta-amyloid protein deposits between nerve cells, which causes deterioration of brain tissue structure and subsequent cell destruction [2][2,25]. As this accumulation progresses, clinical symptoms are classified using the Clinical Dementia Rating (CDR) scale, which ranges from no symptoms (CDR 0) to severe symptoms (CDR 3) [3]. In its later stages, Alzheimer disease severely impairs cognitive and physical abilities, eventually leading to death [4]. While there is presently no cure for Alzheimer's disease, early detection and preventive treatment are critical to delaying symptom development [5], [6].

The beginning stages of Alzheimer symptoms can cause a decline in cognitive function, especially memory loss, which causes someone to forget short term memory loss. Then, in the mild Alzheimer's stage, they will experience symptoms of easy loss of concentration and disorientation. In the moderate stage, they will have difficulty recognizing someone and easily lose control. At the final stage, it can cause difficulty in urinating or swallowing food, difficulty in communicating, and even interfere with someone's behavior and personality. The worst is that it can lead to death [4]. Until now, Alzheimer disease cannot be cured but can prevent the worsening of symptoms through preventive treatment [5. In addition, this disease is dangerous and difficult to prevent. In order to prevent AD, it is crucial to conduct early analysis to detect the disease

and take preventive measures immediately [6]. Early detection of AD can assists healthcare professionals in taking preventive measures against its symptoms. One technique of early detection is the use of brain imaging equipment, that involve magnetic resonance image (MRI) scans [7]. MRI technology enables scans of the brain, including the shrinkage of brain tissue [8].

This research, used an artificial neural network (ANN) as a classification method to predict AD. The selection of the ANN algorithm was chosen because it out perfomed other algorithms tested, including Logistic Regression, Support Vector Machine(SVM) and K-Nearest Neighbor (KNN), in terms of predicted accuracy. This assertion is supported by the findings of Wang et al. [9], who discovered the relative advantages and effectiveness of ANN in predictive scenarios. The research found that the accuracy of the ANN algorithm reached 92.13% higher than the logistic regression algorithm, and it is more comprehensive, cost effective, and accessible than conventional clinical examinations such as computed tomography (CT) scans and MRI scans. The ANN algorithm is large number of interconnected artificial neurons allows for non-linear adaptive processing, enabling the early detection of Alzheimer. The input variables used for the ANN algorithm model in their study include demographic characteristics, behavioral traits, medical history, neuropsychological performance, and biomarkers as reference variables for someone affected by AD.

This research contains research gaps from prior studies. Despite substantial progress in Alzheimer's research, there are still major gaps: Limitations of Conventional Diagnosis Traditional methods of detecting Alzheimer's disease, such as neuropsychological testing and clinical assessments, are time-consuming and expensive, and frequently discover signs at a later stage, limiting prospects for early intervention [7], [8]. Furthermore, reliance on manual MRI interpretation involves subjectivity. This research bridges this gap by utilizing Artificial Neural Networks (ANNs), which provide faster, more objective, and accurate early detection [9]. Limitations in Accuracy and Generalization of Previous Machine Learning Models Previous research employing machine learning methods such as Logistic Regression, Support Vector Machines (SVM), and K-Nearest Neighbor (KNN) revealed problems in addressing complicated and non-linear correlations in data. ANN's adaptive processing capabilities enable greater accuracy, as demonstrated in Alzheimer's prediction [9].

Inadequate Utilization of Open Datasets for Alzheimer Many current studies depend on proprietary datasets, obstructing reproducibility and transparency. This research employs the publicly available Open Access Series of Imaging Studies (OASIS) dataset to enable a reproducible and transparent examination of Alzheimer disease detection [10]. Absence of a Systematic Research Framework in ANN Implementation. Despite the efficacy of ANNs, limited research has employed systematic frameworks like the Cross-Industry Standard Process for Data Mining (CRISP-DM) to direct model creation and assessment. This research employs CRISP-DM to offer a comprehensive and systematic methodology for predicting Alzheimer's disease [26].

Insufficient Emphasis on Early Detection of Alzheimer Disease Research has predominantly concentrated on advanced Alzheimer disease diagnosis rather than early detection, which is essential for effective treatments. This work addresses this gap by highlighting early-stage prediction, employing demographic data, biomarkers, and neuropsychological performance as input variables [6].

This research utilizes Artificial Neural Networks (ANN) as a classification technique to predict Alzheimer's Disease (AD) utilizing the OASIS dataset administered by the Alzheimer's Disease Neuroimaging Initiative (ADNI) [11]. Artificial Neural Networks (ANN) surpass other techniques, including Logistic Regression, Support Vector Machines (SVM), and K-Nearest Neighbors (KNN), in accuracy and adaptability, yielding findings that exceed those of conventional diagnostic procedures [9]. The CRISP-DM framework directs the research through six stages,business understanding, data understanding, data preparation, modeling, implementation [12]. This methodical methodology guarantees an exhaustive examination of Alzheimer’s prognosis and its prospective implementation in preventive measures. This research illustrates the potential of merging artificial intelligence with early diagnostic approaches to enhance Alzheimer's disease management and assist healthcare practitioners in implementing timely preventive interventions. The findings seek to enhance predictive healthcare and elevate the quality of life for persons predisposed to Alzheimer’s disease.

2. Research Methodology

This stage delineates the research phases of the proposed approach utilizing the CRISP-DM framework, commencing with problem formulation, which seeks to articulate and comprehend the research objectives and identify issues grounded in the study context. The subsequent phase is data pre-processing, which guarantees that the data is comprehended and suitable for analysis, resulting in data that is more precise, sanitized, organized, and prepared to yield important insights. The subsequent phase involves modeling,

during which an ANN algorithm is constructed to yield significant insights or precise predictions. The fourth stage entails a discussion of the findings, which encompasses evaluating the ANN modeling results and contemplating their feasibility for prospective real-world implementation or application. The last stage comprises a conclusive statement that encompasses ultimate conclusions and recommendations derived from the study. Each primary level possesses a distinct procedure, visually shown in Figure 1 as a research flowchart. The subsequent subsections will provide a comprehensive account of each stage, encompassing the methodologies and processes employed.

2.1. Dataset

This research employed the Open Access Series of Imaging Studies (OASIS) dataset, overseen by the Alzheimer's Disease Neuroimaging Initiative (ADNI). This dataset offers longitudinal MRI imaging data from persons with and without dementia, designed as an open resource for the global scientific community. The dataset originates from a cooperation with the Washington University Alzheimer's Disease Research Center, Dr. Randy Buckner of the Howard Hughes Medical Institute at Harvard University, and several more contributors [10].

This research utilized the OASIS dataset to create a prediction model for early Alzheimer's detection based on an Artificial Neural Network (ANN). The dataset was partitioned into two subsets: 80% allocated for training and 20% for validation [13]. This division guarantees that the model can learn efficiently from the training data and be assessed optimally on novel data.

2.2. Method

This research seeks to establish a predictive methodology utilizing the ANN algorithm applied to the OASIS Dataset (ADNI). The process commences with problem creation, succeeded by the examination and comprehension of the dataset to elucidate the research dimensions. The data is subsequently analyzed and readied for the modeling phase. The modeling procedure involves partitioning the data into three subsets: training, testing, and validation, while employing K-Fold cross-validation to enhance model correctness. The model findings are assessed and analyzed to draw reliable conclusions, thus leading to the deployment procedure. Figure 1 illustrates the flowchart of the proposed methodology.

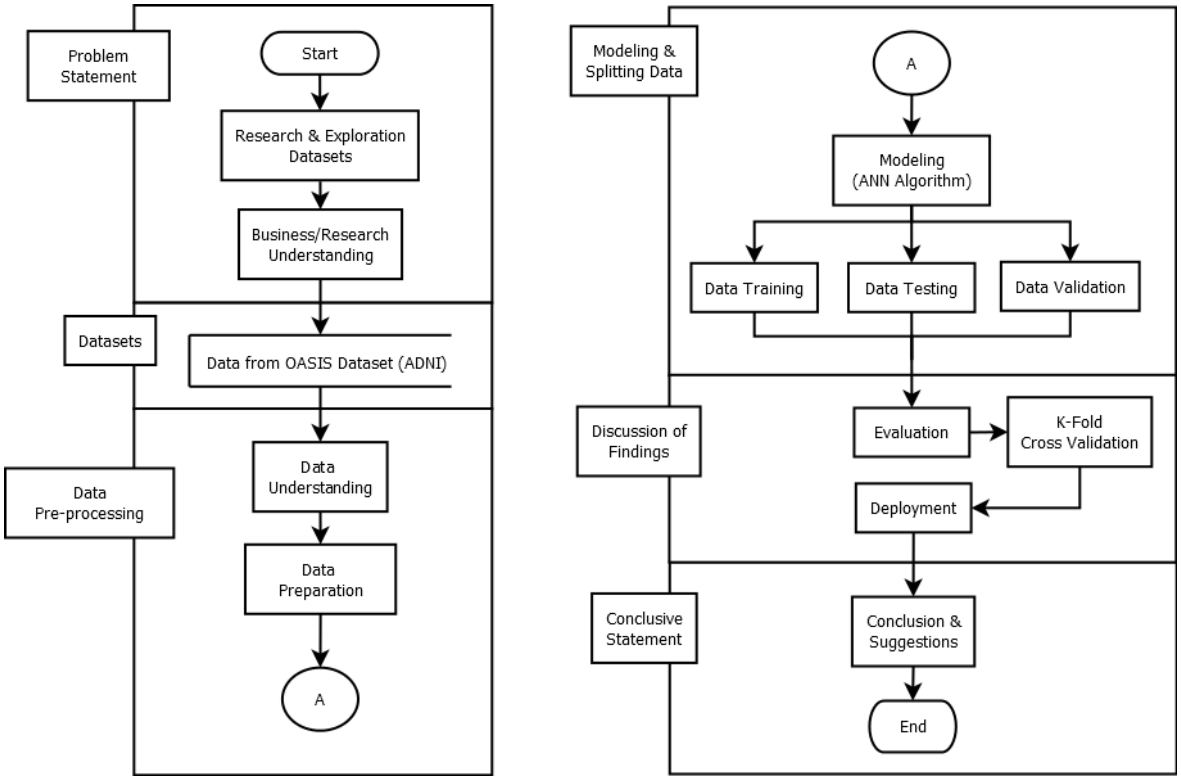

Figure 1. Proposed Method

Following problem definition, dataset exploration seeks to find significant patterns that can provide early insights. The OASIS Dataset, derived from the ADNI (Alzheimer's Disease Neuroimaging Initiative) source, includes a diverse variety of variables such as brain volume, medical history, and demographic factors that may influence the risk of Alzheimer's disease. The investigation phase also includes descriptive statistical analysis and data visualization to identify outliers, trends, or anomalies that could have an impact on the prediction model's accuracy.

Subsequently, preprocessing is conducted to guarantee that the data utilized in modeling is of superior quality. This phase encompasses the management of absent values, data normalization, and feature transformation. Feature selection methods are employed to diminish model complexity and enhance the efficiency of the training process. This method is crucial as ANN necessitate organized and pristine data to yield superior predictions. ANN models are constructed utilizing tailored parameters and designs, including the quantity of hidden layers and the number of neurons within each layer. This procedure is enhanced by K-Fold cross-validation, which mitigates outcome bias and ensures the model generalizes effectively to fresh data.

Measures of accuracy, F1-score, precision, and recall used to assess the model performance. To assess the model's effectiveness in various data settings and in conjunction with other prediction models, a thorough investigation was carried out. The subsequent phase is the deployment process, which seeks to incorporate the model into practical applications.This research ends with a conclusion that summarizes the main results of the project and recommendations for further research. Suggestions include improvements in data collection, more efficient feature selection and the use of more complex machine learning techniques such as ensemble learning for more accurate results.

2.3. Business understanding

Based on the contextualization of this research, several issues concerning Alzheimer disease have been identified, including: The incidence of Alzheimer disease typically manifests in individuals aged 65 years and older, Alzheimer's disease represents a formidable neurodegenerative condition with elusive preventive measures, The progression of Alzheimer's disease leads to an exacerbation of associated symptoms over time, Presently, AD remains incurable, although preventive strategies can be employed to mitigate symptom deterioration.

In response to these challenges, it is crucial to conduct early analysis and detection of AD to promptly implement preventive measures. Early detection facilitates proactive intervention by medical professionals to mitigate the progression of symptoms. Therefore, this research aims to utilize the CRISP-DM approach, specifically employing the ANN classification method, to predict the onset of AD as a preventive measure.

2.4. Data Understanding

This section provides a comprehensive overview of the Longitudinal MRI Data in Nondemented and Demented Older Adults dataset [10] from OASIS MRI datasets, comprising 373 entries distributed across 15 columns. The dataset encompasses 150 individuals between the ages of 60 and 96, consisting of male and female right-handed participants. Among these individuals, 190 is classified as "nondemented," 146 as "demented," and 37 transitioned from "nondemented" to "demented" as a “converted” class during the study period. As shown in Table 1, it presents an overview of the columns included in the dataset utilized for this research.

Table 1. Datasets Column Description

No.	Column Name	Data Type	Description
1.	Subject ID	Object	Containing the identity numbers of the subjects.
2.	MRI ID	Object	Contains the identity number of the MRI test result.
3.	Group	Object	Contains the status of people with Alzhemeir disease.
4.	Visit	Integer	Activity of how many visits or screenings.
5.	MR Delay	Integer	MRI processing delay time.
6.	M/F	Object	Patient Gender.
7.	Hand	Object	More active hands.
8.	Age	Integer	Patient Age.
9.	EDUC	Integer	Patient education or learning period (per Year).
10.	SES	Float	Socioeconomic Status; are represented by values on a scale from 1 to 5, which are used to evaluate an individual's position in relation to economic and social inequality within society [14].
11.	MMSE	Float	Mini Mental State Examination; is widely used to assess cognitive function and is a common tool in the evaluation of dementia. MMSE scores range from 0 to 30, with lower scores indicating a more severe cognitive disorder [15].

12.	CDR	Float	Clinical Dementia Rating; is a crucial measure for evaluating the severity of dementia symptoms in an individual. It typically spans from 0 to 3, with a higher value indicating more severe and chronic symptoms [16].
13.	eTIV	Integer	Estimated Total Incranatial Volume; the total volume inside the human skull, known as the intracranial volume, is an important measurement used in medical research and brain function evaluation [17].
14.	nWBV	Float	Normal Whole Brain Volume; the measurement of the total volume of the brain is utilized for tracking alterations in the overall structure of the brain [18].
15.	ASF	Float	Atlas Scaling Factor; The importance of standardizing the processing of neuroimaging data to examine variations in brain size among contrasting individuals or cohorts [19].

This research investigated data encompassing several demographic, clinical, and volumetric factors related to patients with AD. The data was gathered from research subjects, with distinct identifications documented in the Subject ID and MRI ID fields. This information is essential for effectively maintaining and monitoring each participant's data during the research process.

Whether the subject is a patient with AD or a control group, the Group column indicates the health condition of the subject and guides classification of the subject group. While MR Delay shows the time lag of MRI imaging processing that could influence the observation and diagnosis outcomes, subject activities linked to the number of visits or tests are noted in the Visit column. Gender (M/F) and hand dominance (Hand) are two demographic factors that offer more information to investigate possible effects on brain function. The Age column records the respondents' ages; this information is known to be linked with an aging drop in cognitive ability.

The MMSE (Mini Mental State Examination), a test extensively used to evaluate cognitive state, is one of the primary cognitive evaluation tools in this data. This test's score runs from 0 to 30, lower scores point to more severe cognitive loss. On a range of 0 to 3, the CDR (Clinical Dementia Rating) column gauges the degree of dementia. Higher values suggest more severe and chronic symptoms, which is crucial for patient classification and assessment.

The entire brain volume, indicated as eTIV (Estimated entire Intracranial Volume), can be deduced from the reported volumetric data with nWBV. Medical research and evaluation of cerebral function rely on eTIV; structural alterations in the brain are monitored with nWBV. Neuroimaging standardization is especially beneficial in longitudinal research, utilizing the ASF (Atlas Scaling Factor) column to facilitate the comparison of brain data across multiple people or cohorts.

The purpose of this research is to predict the link between demographic variables, cognitive status, and brain volumetric data with AD progression. A better understanding of these characteristics is expected to lead to new insights into dementia prevention, early detection, and improved patient treatment.

2.5. Data Preparation

The subsequent phase involves data preparation, also known as data preprocessing. Before developing the initial artificial neural network (ANN) models, it is vital to perform exploratory data analysis (EDA) to properly summarize and understand the dataset before integrating it into the model or algorithm [20], [21]. The preliminary phase of the EDA process entails providing a summary of the datasets descriptive statistics. These insights facilitate further investigation by elucidating data patterns. Tables 2 and 3 present the mean, minimum, and maximum values of the datasets.

The subsequent phase involves data preparation, also known as data preprocessing. Before developing the initial ANN) models, it is vital to perform exploratory data analysis (EDA) to properly summarize and understand the dataset before integrating it into the model or algorithm [20], [21]. The preliminary phase of the EDA process entails providing a summary of the datasets' descriptive statistics. These insights facilitate further investigation by elucidating data patterns. Tables 2 and 3 present the mean, minimum, and maximum values of the datasets.

Table 2. First section of the EDA table

	Visit	MR Delay	Age	EDUC	SES
Mean	1.882038	595.104558	77.013405	14.597855	2.460552
Min	1.000000	0.000000	60.000000	6.000000	1.000000
Max	5.000000	2639.000000	98.000000	23.000000	5.000000

Table 3. Last section of the EDA table

	MMSE	CDR	eTIV	nWBV	ASF
Mean	27.342318	0.2980885	1488.128686	0.729568	1.195461
Min	4.000000	0.000000	1106.000000	0.664000	0.876000
Max	30.000000	2.000000	2004.000000	0.837000	1.587000

The MR Delay column, which reflects the MRI processing time lag, has an average of 595.1 days. The minimum value is zero, indicating that some data was acquired without delay, while the greatest value is 2639 days. This broad range may shed light on disparities in imaging data processing and its implications for diagnosis and clinical evaluation outcomes.

The dataset is individuals ages vary widely, with an average of 77 years. The youngest age in this dataset was 60 years, while the oldest was 98 years. This age variability is critical for understanding how aging affects cognitive function and brain health, particularly in the setting of AD and other dementias. Previous research has demonstrated that greater age is associated with a higher risk of cognitive decline, therefore the broad age range in this dataset allows for a more in-depth examination of the relationship.

Education (EDUC) has a mean value of 14.6 years, ranging from 6 to 23 years. This suggests that the subjects in this research come from a variety of educational backgrounds, which is important for evaluating theories about the impact of education on cognitive reserve and resilience to cognitive function decrease. Higher education levels are frequently related with increased cognitive capacity and slower decline, making it a relevant variable to investigate.

Furthermore, socioeconomic status (SES), measured on a scale of 1 to 5, had an average score of 2.46. This result indicates that the majority of individuals had an average economic position, while there was some fluctuation ranging from the lowest (1) to the greatest (5). This variation in socio economic position may provide more information about the impact of social conditions on brain health and access to sufficient health care.

Based on the descriptive statistics results above, reveal an interesting trend in the “Visit” column, with mean value of 1.8 indicating that the majority of data points equal or exceed 1, implying at least one visit. Consequently, the data processed next is the data from the “Visit = 1” column, where there are 150 data points. Following that, the next stage involves performing data cleaning and rectifying imbalances data. The objective is to enhance the accuracy and dependability of modeling results by ensuring that the data used is of high quality, consistency, and relevance [22].

Confirm and ascertain that no columns in the table have empty data. Consequently, eight empty values have been found, particularly in the "SES" column. The subsequent step is removing the eight null values from the dataset. Upon the exclusion of the omitted values, it is necessary to evaluate the revised total, which now consists of 142 data samples after the elimination of 8 null entries from the dataset. Assigning a null value to "SES" dynamically adopts the median value from the "EDUC" column. The selection of the “EDUC” column was predicated on its correlation with the “SES” column, as an individual's educational attainment is frequently influenced by their socio-economic status. This method fosters a more equitable distribution of vacant values, ultimately resulting in a more balanced allocation. It is essential to populate the absent values in the “SES” column utilizing the median value derived from the correlation between the “EDUC” and “SES” columns. Upon completion of the data preparation process, it can be inferred that the data is pristine, coherent, and possesses significant value.

2.6. Modelling

Subsequent to the data preparation phase, the next step entails executing modeling. This research employed machine learning algorithms utilizing artificial neural network (ANN) classification techniques to categorize Alzheimer’s disease. The selected ANN algorithm determined by their ability to incorporate a vast interconnected network of artificial neurons, facilitating non-linear adaptive processing. This method's capacity to model functions without limitations facilitates the representation of events that previously difficult or even unexplained, efficiently and with relative ease [23], [24]. This technique is effective in addressing uncertain or confusing medical information issues, such as the early diagnosis of Alzheimer's disease.

This research utilized the Artificial Neural Network (ANN) algorithm on the Google Colab platform, an integrated cloud-based Jupyter notebook environment. This research will examine feature selection for the ANN algorithm using the independent variables (X) "M/F," "Age," "EDUC," "SES," "MMSE," "eTIV," "nWBV," and "ASF," while the dependent variable (Y) will be "Group." The subsequent procedure entails partitioning the datasets into three segments: 80% designated for the training set, 15% allocated to the test set, and 5% reserved for the validation set. Following the distribution of the datasets, the subsequent essential step is to normalize them to guarantee uniform weighting of value across the features. This modification is crucial for effective ANN modeling due to its sensitivity to fluctuating value weights.

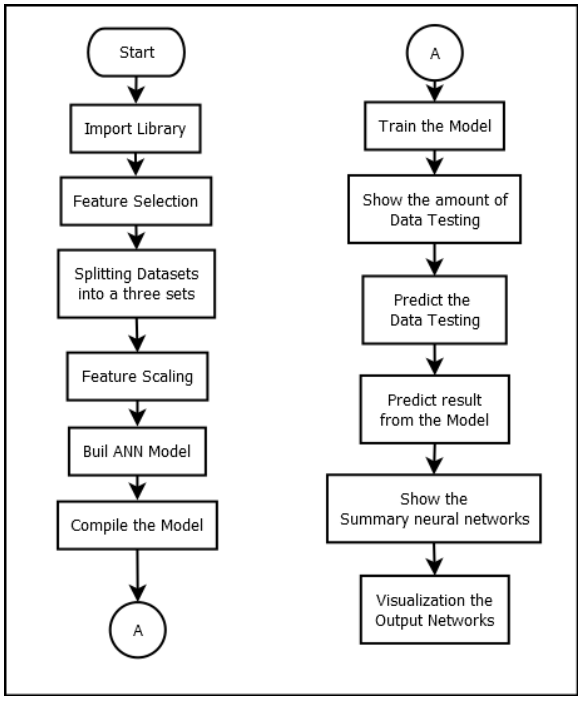

Figure 2. Architecture of the ANN model.

The artificial neural network (ANN) model is constructed with the sequential model object type, which executes a linear neural network. The model comprises three dense layers: the input layer, the hidden layer, and the output layer. The initial two layers employ the rectified linear unit (ReLU) activation function, whereas the third layer utilizes the sigmoid activation function. Subsequently, configure the ANN model with binary cross-entropy functions. The training will comprise 300 iterations with a batch size of 32 samples and 5% of the data allocated for validation. Figure 2 shows the architecture of the ANN model in this research.

This research involved the design and implementation of the Artificial Neural Network (ANN) model architecture, constructed according to the stages depicted in the flowchart. The model development process has several primary steps. The initial stage involves importing pertinent libraries, including TensorFlow, Keras, NumPy, and Pandas, utilized for constructing the ANN model, processing the data, and visualizing the outcomes. The subsequent step Feature selection is conducted to identify the pertinent qualities or variables within the dataset. It seeks to eliminate superfluous or extraneous features, hence enhancing the efficiency and performance of the ANN model. Subsequent action Dividing Datasets into Three Subsets Datasets are categorized into three subsets: the training set for model training, the validation set for parameter fine-tuning, and the testing set for performance evaluation against novel data. This segmentation of datasets guarantees the model's capacity for effective generalization.

Subsequently, Feature Scaling Data is normalized or standardized to provide uniform scaling of all features, hence accelerating the training process and enhancing model accuracy. At this step, techniques such as normalization (range 0-1) or standardization (mean 0, standard deviation 1) are employed. The subsequent phase involves the building of an artificial neural network (ANN) model featuring an input layer, many hidden layers, and an output layer. The quantity of neurons and activation functions in each layer is modified based on the data's complexity and the research aims of the ANN architecture. This work optimizes the model to identify the non-linear patterns in the dataset. The subsequent phase The ANN model is constructed with a loss function of binary cross-entropy to compute the error, an ADAM optimizer to adjust the weights, and an evaluation metric to measure its performance.

The ANN model is subsequently trained with the training dataset. This procedure entails forward propagation to determine the output and backpropagation to adjust the weights according to the computed error. Subsequent to training, testing data is employed to assess the model's performance. This phase guarantees that the volume of testing data is adequate to deliver a representative evaluation of the model's generalization capability.

The trained model is subsequently employed to forecast the outcomes using the testing data. Prediction encompasses classification or regression derived from the provided input dataset. The subsequent stage is to forecast outcomes from the model. The anticipated outcomes derived from the model are juxtaposed with the actual labels to evaluate the model's performance. Techniques such as confusion matrix, precision, recall, and F1-score can be employed to evaluate these outcomes. Subsequent step: Present the Summary of Neural Networks.

The architecture of the ANN model, encompassing the parameter count, inter-neuronal connections, and activation functions employed in each layer, is presented to provide a thorough understanding of the model design.

3. Results and Discussions

Subsequent to the data preparation phase, the next step entails executing modeling. This research employed machine learning algorithms utilizing artificial neural network (ANN) classification techniques to categorize AD. The selected ANN algorithms is determined by their ability to incorporate a vast interconnected network of artificial neurons, facilitating non-linear adaptive processing. This method capacity to model functions without limitations facilitates the representation of events that previously difficult or even unexplained, efficiently and with relative ease [23], [24][. This technique is effective in addressing uncertain or confusing medical information issues, such as the early diagnosis of AD.

3.1. Evaluation

The evaluation stage assesses the effectiveness of the ANN modeling in predicting new data patterns. The evaluation results will undergo analysis using K-fold cross-validation testing to comprehend the model performance. Figure 3 will present a confusion matrix, providing insights into the classification models performance by comparing actual classification results from the datasets.

The model successfully classified data labeled 0 with perfect accuracy, achieving 12 right predictions out of 12 samples, without any errors (false positives or false negatives). Nevertheless, for data originally labeled as 1, the model demonstrated inadequacy by accurately categorizing only 10 samples, while 2 samples erroneously classified as label 0 (false negative). This indicates that the model possesses sufficient sensitivity, yet, there is potential for enhancement in identifying positive labels (label 1). This evaluation using the confusion matrix demonstrates that the model excels at classifying label 0 (high precision) but necessitates enhancement to augment the recall of label 1, hence improving its efficacy in addressing positive cases. This evaluation is crucial for analyzing the equilibrium of the model performance and verifying its capability to manage imbalances in the categorization data. Utilizing the data from the confusion matrix enables the calculation of evaluation metrics such as accuracy, precision, recall, and F1-score. Accuracy evaluates the model overall performance in predicting all classes, precision assesses the correctness of the requested data relative to the model's predictions, while recall indicates the model's capacity to accurately identify all true positive cases. The F1-score represents the harmonic mean, integrating precision and recall into a singular balanced metric. The table will display the macro average metric and the weighted average metric. This metric will provide a more comprehensive knowledge of the performance of categorization models. The modeling produces a categorization report displayed in Table 4, which offers a comprehensive examination.

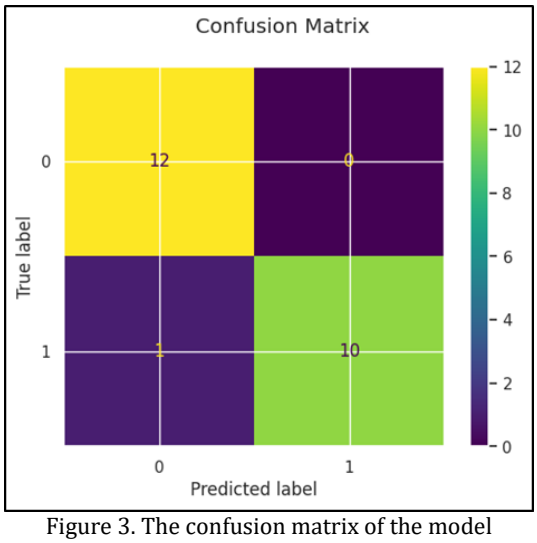

Figure 3. The confusion matrix of the model

Table 4. Classification report

	Precision	Recall	F1-score
0	0.92	1.00	0.96
1	1.00	0.91	0.95
Accuracy			0.96
Macro Avg	0.96	0.95	0.96
Weighted Avg	0.96	0.96	0.96

Analysis of the classification report, presented in the tables, reveals exceptional performance across all evaluation metrics. The model demonstrates high precision, with a score of 0.92 for the negative class and a perfect score of 1.00 for the positive class, indicating its ability to flawlessly identify positive instances. Similarly, the recall values achieve a perfect score of 1.00 for the negative class and a value of 0.91 for the positive class, signifying the model's effectiveness in capturing the majority of positive cases. Furthermore, the F1-scores of 0.96 and 0.95 for the negative and positive classes, respectively, demonstrate a well-balanced performance between precision and recall. Notably, the overall accuracy of the ANN model is a remarkable 0.96, highlighting its proficiency in Alzheimer's disease prediction. Additionally, both macro and weighted averages exhibit strong performance, with scores of 0.96 for precision, 0.95 for recall (macro), and 0.96 across all metrics (weighted).

3.2. K-fold Cross Validation

The proposed model attained an impressive accuracy of 96% on the initial training set; however, to guarantee its robustness and generalizability in predicting Alzheimer's disease, we utilized K-fold cross-validation, a method that reduces overfitting and offers a more dependable assessment of the model's performance on unseen data. This method entails partitioning the dataset into K equal-sized segments and systematically employing one segment for testing while utilizing the remaining K-1 segments for training. The performance indicators are subsequently averaged across all K folds to yield an impartial estimate of the model's generalization performance. The specific parameters of the K-fold cross-validation method are delineated in Table 5.

K-fold cross-validation was executed with K set to 10, indicating that the data was partitioned into 10 segments or folds. This procedure utilized an enabled shuffle to guarantee an even distribution of data within each fold, employing a random state value of 42 to assure result reproducibility. The model underwent training for 300 epochs each fold, utilizing a batch size of 32. The parameters selected to enhance the model's performance and accuracy during training.

The Table 6 presents the test accuracy performance for each fold of the K-fold cross-validation. This table enables the computation of the mean accuracy across all K-folds, offering a thorough evaluation of the performance of the proposed ANN models. The K-fold cross-validation findings illustrate the exceptional efficacy of the ANN algorithm in forecasting Alzheimer's illness. The model demonstrates robust prediction ability, achieving an average accuracy of 90.7% across 10 folds. The model attained flawless accuracy of 100% in folds K-6, K-8, K-9, and K-10, underscoring its proficiency in comprehending and assimilating the data patterns within each fold.

Table 5. Parameters of K-fold cross-validation

Parameter	**Description**
K (train set)	10
Shuffle	True
Epoch	300
Random State	42
Batch Size	32

Table 6. K-fold cross-validation accuracy.

K (train set)	Accuracy
1	76.92307829856873
2	76.92307829856873
3	76.92307829856873
4	92.30769276618958
5	92.30769276618958
6	100.0
7	92.30769276618958
8	100.0

9	100.0
10	100.0
Accuracy Avg	90.76923131942749

3.3. Deployment

The deployment phase seeks to execute and oversee the research model formulated and evaluated in prior phases inside the operational setting. This phase emphasizes the model's capacity to provide enduring business value. Essential actions during the deployment phase encompass deployment planning, implementation, monitoring, and assessment. Documentation produced during the deployment phase comprises user manuals, model performance reports, validation studies, and monitoring and evaluation plans.

4. Conclusion

The objective of this investigation was to construct a prediction model for Alzheimer's disease within the CRISP-DM framework by employing the Artificial Neural Network (ANN) classification method. The research data was acquired from the OASIS and subjected to preprocessing techniques in order to enhance its quality. The ANN model that was developed obtained a precision of 1.00 and a recall of 0.91 for the Alzheimer's class, and a precision of 0.92 and a recall of 1.00 for the non-Alzheimer's class. The f1-score for both classes was also high, with the Alzheimer's class having a score of 0.95 and the non-Alzheimer's class having a score of 0.96. The ANN model was able to accurately identify Alzheimer's disease with a 96% accuracy rate. The model's consistent and robust performance in predicting Alzheimer's disease was exhibited by an average performance of 90.7% across 10 iterations in K-fold cross-validation testing.

The results of this research indicate that the Alzheimer's disease prediction model, which employs the ANN classification method within the CRISP-DM framework, can be effectively implemented to facilitate the early diagnosis of Alzheimer's disease. This is due to the ANN model's exceptional performance in predicting Alzheimer's disease and the data pre-processing that improved data quality. This investigation contributes to the advancement of Alzheimer's disease prediction models that are both precise and efficient. The model that has been proposed has the potential to aid clinicians in the early diagnosis of Alzheimer's disease and to facilitate the opportune intervention of patients. Additional research is necessary to assess the model on a broader population and to create a more comprehensive model that integrates supplementary risk factors for Alzheimer's disease.

Present your research conclusions based on the methodology, results, and discussions presented previously. The conclusion should be concise and comprehensive, including all research results. You may also present numerical results as empirical evidence of your findings. Finally, convey the disadvantages of your research or what has not been resolved during the study or future research considered.

References

[1] A. Atri, “The Alzheimer’s Disease Clinical Spectrum: Diagnosis and Management,” *Medical Clinics of North America*, vol. 103, no. 2, pp. 263–293, Mar. 2019, doi: 10.1016/J.MCNA.2018.10.009.

[2] J. Povova *et al.*, “Epidemiological of and risk factors for Alzheimer‘s disease: A review,” *Biomedical Papers*, vol. 156, no. 2, pp. 108–114, 2012, doi: 10.5507/BP.2012.055.

[3] J. C. Morris, “The Clinical Dementia Rating (CDR): current version and scoring rules,” *Neurology*, vol. 43, no. 11, pp. 2412–2414, 1993, doi: 10.1212/WNL.43.11.2412-A.

[4] Z. Breijyeh, R. Karaman, D. Muñoz-Torrero, and R. Dembinski, “Comprehensive Review on Alzheimer’s Disease: Causes and Treatment,” *Molecules*, vol. 25, no. 24, p. 5789, Dec. 2020, doi: 10.3390/MOLECULES25245789.

[5] J. C. De La Torre, “Alzheimer’s Disease is Incurable but Preventable,” *Journal of Alzheimer’s Disease*, vol. 20, no. 3, pp. 861–870, May 2010, doi: 10.3233/JAD-2010-091579.

[6] J. Rasmussen and H. Langerman, “Alzheimer’s Disease – Why We Need Early Diagnosis,” *Degenerative Neurological and Neuromuscular Disease*, vol. 9, pp. 123–130, Dec. 2019, doi: 10.2147/DNND.S228939.

[7] H. A. Helaly, M. Badawy, and A. Y. Haikal, “Deep Learning Approach for Early Detection of Alzheimer’s Disease,” *Cognitive Computation*, vol. 14, no. 5, pp. 1711–1727, Sep. 2022, doi: 10.1007/S12559-021-09946-2/FIGURES/15.

[8] E. Moradi, A. Pepe, C. Gaser, H. Huttunen, and J. Tohka, “Machine learning framework for early MRI-based Alzheimer’s conversion prediction in MCI subjects,” *NeuroImage*, vol. 104, pp. 398–412, Jan. 2015, doi: 10.1016/J.NEUROIMAGE.2014.10.002.

[9] N. Wang, J. Chen, H. Xiao, L. Wu, H. Jiang, and Y. Zhou, "Application of artificial neural network model in diagnosis of Alzheimer's disease," *BMC Neurology*, vol. 19, no. 1, pp. 1–8, Jul. 2019, doi: 10.1186/S12883-019-1377-4/TABLES/6.

[10] D. S. Marcus, T. H. Wang, J. Parker, J. G. Csernansky, J. C. Morris, and R. L. Buckner, "Open Access Series of Imaging Studies (OASIS): Cross-sectional MRI Data in Young, Middle Aged, Nondemented, and Demented Older Adults," *Journal of Cognitive Neuroscience*, vol. 19, no. 9, pp. 1498–1507, Sep. 2007, doi: 10.1162/JOCN.2007.19.9.1498.

[11] D. S. Marcus, A. F. Fotenos, J. G. Csernansky, J. C. Morris, and R. L. Buckner, "Open Access Series of Imaging Studies: Longitudinal MRI Data in Nondemented and Demented Older Adults," *Journal of Cognitive Neuroscience*, vol. 22, no. 12, pp. 2677–2684, Dec. 2010, doi: 10.1162/JOCN.2009.21407.

[12] F. Provost and T. Fawcett, *Data Science for Business: What You Need to Know about Data Mining and Data-Analytic Thinking*. CA: O'Reilly Media, 2013.

[13] S. J. B. Vos *et al.*, "Preclinical Alzheimer's disease and its outcome: A longitudinal cohort study," *The Lancet Neurology*, vol. 12, no. 10, pp. 957–965, Oct. 2013, doi: 10.1016/S1474-4422(13)70194-7.

[14] G. Navarro-Carrillo, M. Alonso-Ferres, M. Moya, and I. Valor-Segura, "Socioeconomic Status and Psychological Well-Being: Revisiting the Role of Subjective Socioeconomic Status," *Frontiers in Psychology*, vol. 11, p. 543258, Jun. 2020, doi: 10.3389/FPSYG.2020.01303/BIBTEX.

[15] I. Arevalo-Rodriguez *et al.*, "Mini-Mental State Examination (MMSE) for the early detection of dementia in people with mild cognitive impairment (MCI)," *Cochrane Database of Systematic Reviews*, vol. 2021, no. 7, Jul. 2021, doi: 10.1002/14651858.CD010783.PUB3/MEDIA/CDSR/CD010783/IMAGE_T/TCD010783-TST-003.PNG.

[16] J. E. Tan, E. Strauss, and E. M. S. Sherman, "Clinical Dementia Rating," *Encyclopedia of Clinical Neuropsychology*, pp. 803–806, 2018, doi: 10.1007/978-3-319-57111-9_533.

[17] S. Sargolzaei *et al.*, "Estimating Intracranial Volume in Brain Research: An Evaluation of Methods," *Neuroinformatics*, vol. 13, no. 4, pp. 427–441, Oct. 2015, doi: 10.1007/S12021-015-9266-5/METRICS.

[18] M. Kijonka *et al.*, "Whole Brain and Cranial Size Adjustments in Volumetric Brain Analyses of Sex- and Age-Related Trends," *Frontiers in Neuroscience*, vol. 14, p. 509955, Apr. 2020, doi: 10.3389/FNINS.2020.00278/BIBTEX.

[19] L. V. Fulton, D. Dolezel, J. Harrop, Y. Yan, and C. P. Fulton, "Classification of Alzheimer's Disease with and without Imagery Using Gradient Boosted Machines and ResNet-50," *Brain Sciences*, vol. 9, no. 9, p. 212, Aug. 2019, doi: 10.3390/BRAINSCI9090212.

[20] D. Galatro and S. Dawe, "Exploratory Data Analysis," in *Data Analytics for Process Engineers. Synthesis Lectures on Mechanical Engineering*, Springer, Cham, 2024, pp. 13–57.

[21] A. T. Jebb, S. Parrigon, and S. E. Woo, "Exploratory data analysis as a foundation of inductive research," *Human Resource Management Review*, vol. 27, no. 2, pp. 265–276, Jun. 2017, doi: 10.1016/J.HRMR.2016.08.003.

[22] C. McCue, "Process Models for Data Mining and Predictive Analysis," in *Data Mining and Predictive Analysis*, Butterworth-Heinemann, 2015, pp. 51–74.

[23] S. B. Maind and P. Wankar, "Research Paper on Basic of Artificial Neural Network," *International Journal on Recent and Innovation Trends in Computing and Communication*, vol. 2, no. 1, pp. 96–100, Jan. 2014, doi: 10.17762/IJRITCC.V2I1.2920.

[24] M. Mishra and M. Srivastava, "A view of Artificial Neural Network," 2014, doi: 10.1109/ICAETR.2014.7012785.